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Noise Signal Classification for Oil Condition Monitoring Using Neural Network

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Abstract

This paper describes a motor oil condition monitoring system that uses wavelet transform and neural network techniques.Experiments were conducted using motor oils with different mileage in the gear mechanism. The gear noise signals were acquired using a data acquisition system and feature extraction using discrete wavelet transform. The discrete wavelet transform extracts the features for use as the input signals for a neural network. The motor oil condition classification is determined using an artificial neural network.According to the laboratory obtained experimental results the average recognition rate is about 90%.Therefore, the condition monitoring system can be achieved using Wavelet Transform and Neural Networks Techniques.

Keywords

Wavelet Transform; Neural Network;Motor Oil; Noise; Probabilistic Neural Network

Introduction

Engine overheating and motor oil degradation are major causes of car engine damage. The major functions of motor oil in the engine are lubrication, cleaning, cooling, sealing, corrosion protection and noise reduction. However, with the engine at high temperature during long high work load periods, the motor oil gradually darkens, viscosity increases, lubrication decreases and oxidation causes oil deterioration. The motor oil condition has great influence on the engine's lifespan. Therefore, the motor oil change interval is particularly important. Owner's manuals have traditionally suggested changing the motor oil should whenever the vehicle reaches a predetermined mileage or a specified time interval,whichever comes first.In recent years an increasing number of low emission vehicles were launched in succession, especially hybrid cars. The previous motor oil change intervals will therefore not satisfy the periodic engine maintenance schedule.

The water concentration in motor oil will affect the oil’s conductivity. When sensor elements are oscillated at high frequencies an electrostatic field signal is formed between them. This signal is used to determine the motor oil life span [1]. Different viscosity motor oils will not produce the same oil pressure in the oil galleries.The sensor elements can utilize the oil pressure information to estimate the viscosity of engine oil and determine the motor oil degradation and engine oil replacement schedule [2].This article proposes using different noise characteristics to identify the motor oil condition to provide motorists with more accurate motor oil replacement timing.This experimental study collected motor oil at different degradation degrees.This degraded oil was processed through noise signal acquisition equipment.The experimental results demonstrate that the noise signal is a workable analytical tool

Noise Signal Feature Extraction

The Fourier transform has a serious drawback in that it will lose the time information when it is transformed from the time domain into the frequency domain. If the signal is stable, there will not be much impact. However, most of the signals is not stable and it also contains a number of important message features. The Wavelet Analysis and the Short-time Fourier analysis utilize different window function frames. It can change the frame size in order to determine the time or frequency more accurately. The literature on wavelet theory first appeared in 1910 proposed by Haar. They used wavelet theory to analyze the horizontal and diagonal details of seismic data [3]. The first

contribution was by Daubechies in the construction of a discrete wavelet basis in the 1980s [4]. The signal energy of each scale in the eight layers is determined using discrete wavelet decomposition, as shown in Figure 1. The amount of data in the original signal is reduced using the discrete wavelet transform, allowing the computer to reduce the computation time. Therefore, discrete wavelet transform was used to extract the motor oil noise features in this experiment.

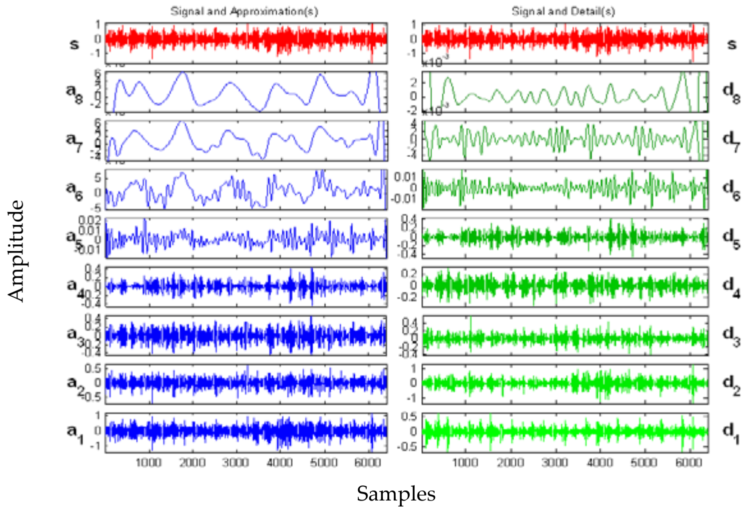

FIG. 1THE SIGNAL ENERGY OF EACH SCALE IN THE EIGHT LAYERS

Principles of Neural Network Classification

Radial Basis Function Neural Network

The radial basis function concept was first proposed by Broomhead and Lowe in 1988 [5]. The radial basis function neural network (RBFNN) has many uses, including function approximation, classification and prediction [6]. The RBFNN architecture consists of three layers, an input layer, a hidden layer (Radial basis function layer) and an output layer (linear layer) [7]. The radial basis layer has s^1 neurons, $\|dist\|$ is the Euclidean distance between the weighting matrix $IW^{1,1}$ and the input vector P. The output layer a^1 is obtained by multiplying $\|dist\|$ by b^1 (Bias weight vector) element. In radial basis layer each neuron produces value according to its Euclidean distance. If the distance is the greater its value is closer to zero, conversely, the value will be closer to 1 if the distance is smaller. The transfer functions are usually in the hidden layer and this is a non-linear Gaussian function. We can change the sensitivity of neurons by using a bias weight b^1 to adjust the value. It will output the values to the linear layer on further classification.

Probabilistic Neural Network

The probabilistic neural network (PNN) is a variation of the RBF neural network [8]. It was widely used in monitoring systems to resolve classification questions. PNN belongs to the feed-forward neural network architecture type and employs Bayesian decision theory. Its advantage lies in the use of a linear learning algorithm to complete the work done by non-linear algorithms. It can maintain the accuracy of a nonlinear algorithm. Real-time network training is the most important feature in the architecture. It is therefore suitable for use in real-time systems with fault type classification. The radial basis layer operates from the input vector to the training vectors to calculate Euclidean distance and produce a vector. The next layer sums the contributions of each type of input to produce a probability vector as the net output. The transfer function on the competition layer output selects the maximum value of these probabilities via competition. When the output value is 1 it indicates the desired categories. If the output value is 0 it indicates other species.

General Regression Neural Network

The generalized regression neural network (GRNN) by D. F. Specht was published in 1991 [9]. It is the same as the

PNN, obtaining a good prediction with just a small number of training samples. The GRNN has a fast learning speed and powerful nonlinear mapping ability, and is therefore commonly used in function approximation and fault detection [10]. It has a radial basis layer and a special linear layer. The GRNN has Q input vectors with each group having R vector elements and Q neurons in the middle layer. It has as many neurons as input/destination vectors in the second layer. The nprod box (code function normprod) has $LW^{2,1}$ with input vector a^2 of the inner product. It is used as a special linear transfer function to classify.

Experimental Methods and Analysis

In order to understand the oil condition at various mileages, oil sample were collected from engines with the engine mileage and oil residence time known. There are many external variables that may affect the experimental results. For example, the oil viscosity will affect the sound characteristics of mechanical moving parts. Therefore, in order to obtain more accurate results, this experimental equipment must also formulate the oil capacity, oil temperature and motor speed.

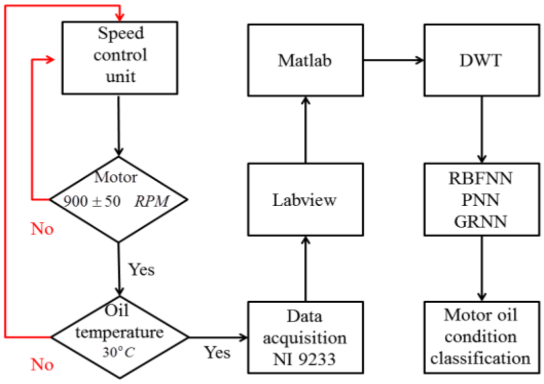

FIG. 2FLOW CHART OF EXPERIMENTAL PROCEDURE AND SIGNAL PROCESSING

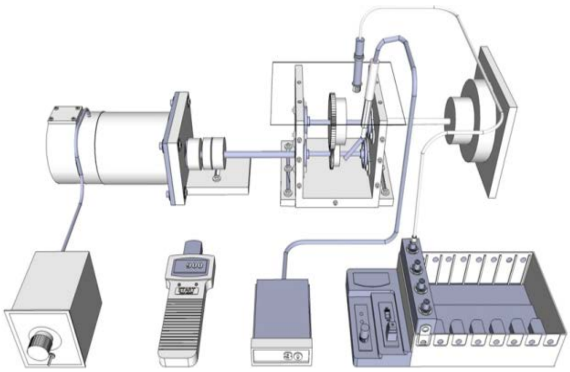

FIG. 3EXPERIMENTAL PLATFORM DIAGRAM

Experimental Platform and Procedure

To ensure accurate data collection specific conditions settings were adopted.The experimental platform is shown in Figure 2.This experiment are used a conventional sedan, driven under normal driving conditions on normal roads, including urban roads and freeways. The motor oil was collected after driving every 1000 ± 50 kilometers. The oil was placed into a transparent gearbox for signal acquisition, as shown in Figure 3. In this experiment we added 500 ml of motor oil to the experimental platform, then started the electric motor using an optical tachometer to monitor the electric motor's speed. A speed controller was used to control the motor rotational speed at 900 ± 50 RPM (Revolutions per minute). At this time the oil temperature was monitored using a thermocouple thermometer. The motor oil temperature was set at 30 degrees Celsius.

A microphone was used to capture the crankcase mechanical running sound signals. The signals were then processed through a NI (National Instruments) data acquisition card for signal processing and sent via USB (Universal Serial Bus) to a PC (Computer). These voltage signals were converted into document files using the Labview software to facilitate subsequent operations.

The effective sampling frequency was 20 kHz (kilo-Hertz) at 20000 samples per second using a 1 second sampling time. The collected signals were processed using Matlab software to perform FFT analysis. The signal frequency energy was very small at approximately 3 kHz. This experiment therefore set the sampling frequency at 6.4 kHz with a sampling time of 1 second for the subsequent a data capture condition. The signal feature extraction method used MATLAB to perform signal DWT. Table 1 shows the frequency distribution after DWT in each frequency band. This experiment collected motor oil used in driving distances of 1000, 2000, 3000, 4000 and 5000 kilometers. These frequency scales have many overlapping frequency bands, therefore nine kinds of non-overlapping frequency scales were used in these experiments as the feature data.

TABLE1FREQUENCY DISTRIBUTION AFTER DWT IN EACH FREQUENCY SCALS

Low-pass filters (Approximations)			**High-pass filters** (Details)		
Level (A)	**Frequency band** (Hz) $(f_n = 3200\ Hz)$		**Level** (D)	**Frequency band** (Hz) $(f_n = 3200\ Hz)$	
1	0~1600	$0 \sim f_n/2^1$	1	1600~3200	$f_n/2^1 \sim f_n$
2	0~800	$0 \sim f_n/2^2$	2	800~1600	$f_n/2^2 \sim f_n/2^1$
3	0~400	$0 \sim f_n/2^3$	3	400~800	$f_n/2^3 \sim f_n/2^2$
4	0~200	$0 \sim f_n/2^4$	4	200~400	$f_n/2^4 \sim f_n/2^3$
5	0~100	$0 \sim f_n/2^5$	5	100~200	$f_n/2^5 \sim f_n/2^4$
6	0~50	$0 \sim f_n/2^6$	6	50~100	$f_n/2^6 \sim f_n/2^5$
7	0~25	$0 \sim f_n/2^7$	7	25~50	$f_n/2^7 \sim f_n/2^6$
8	0~12.5	$0 \sim f_n/2^8$	8	12.5~25	$f_n/2^8 \sim f_n/2^7$

Motor Oil Condition Identification

The noise signal is first processed through DWT to produce the characteristic energy signal. The characteristic energy signal is then input to the RBF, GRNN and PNN. Training and classification are conducted by three Neural Network types for the condition monitoring system.All designated characteristic signal mileage conditions are divided into six kinds, unused motor oil, and oil used for 1000, 2000, 3000, 4000 and 5000 kilometers of driving. Each type of collected motor oil has 62 group characteristic signal data sets, with a total of 372 group characteristic data sets used as the neural network training and testing input data. The experiment uses outside tests method independently employing training group and test group data. Each independently, the training group data was not placement in test group data. The Characteristic signals of each specified mileage uses the 2 group data as the training group and 60 group data as the test group.

In this experiment a thousand different types of parameter adjustments are made, with these parameter values ranging from one-thousandth to one respectively. PNN and GRNN via the adjustable parameters have the same best recognition rate of 93.06%, while the RBFNN best recognition rate is close to 90% as shown in Table 2.

TABLE2 RECOGNITION OF DIFFERENT NEURAL NETWORK TYPES

	RBF	GRNN	PNN
0 km	91.67	95	95
1000 km	90	88.33	88.33
2000 km	96.67	98.33	98.33
3000 km	70	90	90
4000 km	90	88.33	88.33
5000 km	98.33	98.33	98.33
Average	89.44	93.06	93.06

Conclusion

In this experiment we used sound characteristics to distinguish motor oil using situation. Wavelet analysis is used first to make feature extraction, followed with using the RBF, PNN and GRNN neural networks for classification. This method is theoretically feasible and can provide accurate motor oil deterioration condition. This monitoring system can be used to prevent overuse of motor oil, and prevent wear and damage of internal engine parts. Understanding the motor oil drain intervals can reduce motor oil consumption, save resources and reduce car maintenance costs. If the apparatus can be used in actual vehicle or equipment to do the testing, collecting a greater oil mileage will be more satisfactory.

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